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CONSISTENT DIRECTIONS OF THE LEAST SQUARES ESTIMATORS IN LINEAR MODELS

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ABSTRACT

The consistent directions of the least squares estimators in a linear model are defined to be the linear combinations of parameter estimates that are asymptotically consistent. When the design variable is univariate and the regression function is smooth, consistent directions are characterized in previous papers (Wu, 1980; Wu and Wang, 1982) in terms of the convergence rates of the design sequence to its limit points. Extensions of these results to multivariate design variables are considered in the present paper.

AMS (MOS) Subject Classifications: Primary 62J05, Secondary 62E20

Key Words: Asymptotic consistency, Consistent direction, Least squares estimators, Multiple linear regression, Multiple polynomial regression

Work Unit Number 4 (Statistics and Probability)

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SIGNIFICANCE AND EXPLANATION

A basic requirement of the least squares estimator in a linear model is that it should be close to the true parameter for a large sample size. If this is not the case, one would like to know what linear combinations of the components of the least squares estimator are close to their counterparts in the parameter. In this paper we study the characterization of these combinations for linear models with smooth regression functions and multivariate input variables.

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CONSISTENT DIRECTIONS OF THE LEAST SQUARES ESTIMATORS IN LINEAR MODELS Song-Gui Wang* and C. F. Jeff Wu

1. Introduction

Consider a linear model

$$y = \theta'f(x) + \varepsilon$$
 (1.1)

where $\theta' = (\theta_1, \dots, \theta_p)$, $\xi'(x) = (f_1(x), \dots, f_p(x))$, $f_j(x)$, $j = 1, \dots, p$, are univariate functions of the input vector $x = (x_1, \dots, x_q)^T$, the random error $x = (x_1, \dots, x_q)^T$, the random error $x = (x_1, \dots, x_q)^T$, the random error $x = (x_1, \dots, x_q)^T$, and $x_1 = (x_1, \dots, x_q)^T$ is observed at $x_1 = (x_1, \dots, x_q)^T$, and $x_1 = (x_1, \dots, x_q)^T$ is of full rank, the least squares estimator (LSE) of $x = (x_1, \dots, x_q)^T$

$$\hat{\theta} = (\mathbf{x}_n^* \mathbf{x}_n)^{-1} \mathbf{x}_n^* \mathbf{y} , \qquad (1.2)$$

where $y' = (y_1, \dots, y_n)$. It is known that $\hat{\theta} + \hat{\theta}$ a.s. (or in prob.) iff $(x_n^* x_n)^{-1} + 0$ when $\{\varepsilon_i\}_1^n$ are i.i.d. (or uncorrelated). The strong consistency part was proved in Lai et al. (1979). For recent results on the consistency of LSE, see the references of Wu (1980) and Wu and Wang (1982). In case $(x_n^* x_n)^{-1} + 0$ does not hold, $\hat{\theta}$ is not consistent for estimating the vector $\hat{\theta}$. It was observed in Wu (1980) that, in this case, the best linear unbiased estimator $\hat{b}^* \hat{\theta}$ of a linear combination $\hat{b}^* \hat{\theta} = \sum_{i=1}^{p} b_i \theta_i$ may still be consistent for some vectors \hat{b} . Such a vector \hat{b} is called a <u>consistent direction</u> of the LSE $\hat{\theta}$. The space of consistent directions is defined as

$$S(\xi) = \{ \hat{p} : \hat{p}_{i}(x_{i}^{u}x_{i}^{u})_{-1} \hat{p} = \hat{p}_{i}(\sum_{i=1}^{l} \xi(\hat{x}^{i})\xi(\hat{x}^{i})_{i})_{-1} \hat{p} + 0 \text{ as } u + \infty \}.$$

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A general characterization of $S(\xi)$ as given in Wu (1980). When the input x is scalar (q = 1 in (1.1)) and f_j is any smooth function in x, a more refined characterization was given in Wu and Wang (1982) in terms of the convergence rates of the design sequence to its limit points. More specifically, if a is a limit point, i.e., there exists a subsequence $x_{n_1} + a$ as $i + \infty$, and $\sum_{i=1}^{\infty} (x_{n_1} - a)^{2r} = \infty$, the r^{th} derivative $\xi^{(r)}(a)$ is a consistent direction under some smoothness assumption on $\xi(x)$ near a. Extension of this result to multivariate input x is nontrivial because different components of the vectors x_{n_1} may converge to their limit points at different rates. A simple special case (constant convergence rate for all components) was considered in Wu and Wang (1982). The purpose of this paper is to present more general results for the multivariate input variable x.

The mathematical results developed in the three papers may find applications beyond the consistency of LSE. For the convenience of the potential users of our results, we will give this problem an equivalent formulation that is void of statistical jargons.

A. Given a sequence of $p \times 1$ vectors $\{\underline{y}_i\}_1^m$, characterize the subspace $S = \{\underline{b} : \underline{b}^*(\sum_{i=1}^n \underline{y}_i\underline{y}_i^*)^{-1}\underline{b} + 0 \text{ as } n + m\} \text{ in terms of the "limiting" behavior of } \{\underline{y}_i\}_1^m.$

B. If ψ_i is a smooth function of a $q \times 1$ vector ψ_i , i.e. $\psi_i = \xi(\psi_i)$ and ξ is smooth, characterize the subspace S defined in A in terms of the "limiting" behavior of the input sequence $\{\psi_i\}_{i=1}^{\infty}$. Typically q is much smaller than p.

Problem A was solved in Wu (1980). Problem B was solved for some f functions and input variables w in Wu (1980), Wu and Wang (1982) and the present paper.

2. Main results

Before stating the main results, we define some notations. We assume that the input sequence $\{x_i\}_1^{\infty}$ is bounded, where $x_i^* = (x_{i1}, \dots, x_{iq})$. The less interesting case that $\{x_i\}_1^{\infty}$ is unbounded can be treated as in Wu (1980). If there exists an infinite subsequence n_i such that $x_{n_i} + a_i$ as $i + \infty$, we say that a_i is a limit point of $\{x_i\}_1^{\infty}$. Define $N(a,\delta)$, the δ -neighborhood of $a_i^* = (a_1,\dots,a_q)$, to be $\{x_i^* = (x_1,\dots,x_q): |x_i^* - a_i| < \delta, i = 1,\dots,q\}$, and $C^T(a,\delta)$ to be the set of functions with x^{th} continuous partial derivatives in $N(a,\delta)$. In particular, $c^0(a,\delta)$ is the set of continuous functions in $N(a,\delta)$. Define $f(x) \in C^T(a,\delta)$ iff $f_i(x) \in C^T(a,\delta)$ for $1 \le i \le p$. The little o-notation $u_n = o(v_n)$ means $|u_n|/|v_n| + 0$ as $n + \infty$.

Define
$$(x - a)^{\nabla} = \sum_{i=1}^{q} (x_i - a_i) \frac{\partial}{\partial x_i}$$
,

$$[(x - a)^{\nabla}]^k \xi(a) = ([(x - a)^{\nabla}]^k f_1(a), \dots, [(x - a)^{\nabla}]^k f_p(a))^*$$

$$= \sum_{\xi_k \in T_k} (x_{j_1} - a_{j_1}) \dots (x_{j_k} - a_{j_k}) \frac{\partial^k \xi(a)}{\partial x_{j_1} \dots \partial x_{j_k}}, \quad (2.1)$$

$$s_i(k,t) = \frac{y^i [(x_{n_i} - a)^{\nabla}]^k \xi(a)}{k! (x_{n_i} t - a_t)^k} \quad (2.2)$$

and

$$s_{i}(r,t,A) = \psi' \sum_{\xi_{r} \in A} (x_{n_{i}j_{1}-a_{j_{1}}}) \cdots (x_{n_{i}j_{r}-a_{j_{r}}}) \frac{\partial^{r} \xi(a)}{\partial x_{j_{1}} \cdots \partial x_{j_{r}}} / [ri(x_{n_{i}t}-a_{t})^{r}], \qquad (2.3)$$

where $\xi_k = (j_1, \dots, j_k)$,

$$T_k = \{\xi_k = (j_1, \dots, j_k) : 1 \le j_m \le q, 1 \le m \le k\},$$
 (2.4)

and A is a subset of T_r , k = 1, ..., r.

Suppose $\{J_{g}\}_{g=1}^{3}$ is a partition of $J=\{1,2,\ldots,q\}$. Define a partition of T_{r} as follows:

$$T_{r1} = \{ \underline{\xi}_r = (j_1, \dots, j_r) \in T_r : j_m \in J_1 \cup J_2 \text{ for all } m \text{ and } j_m \in J_1$$
 for at least one $m \}$, (2.5)

$$T_{r2} = \{\xi_r = (j_1, ..., j_r) \in T_r : j_m \in J_2 \text{ for all } m\},$$
 (2.6)

$$T_{r3} = \{\xi_r = (j_1, \dots, j_r) \in T_r : j_m \in J_3 \text{ for at least one } m\}.$$
 (2.7)

We are now in the position to state the main theorems.

Theorem 1. If $f(x) \in C^0(a,\delta)$ for some $\delta > 0$, then f(a) is a consistent direction for any limit point a of the design sequence $\{x_i\}_{i=1}^m$.

This follows immediately from Theorem 2 of Wu (1980).

Theorem 2. Suppose

- (i) $x_{n_{\underline{i}}} + a_{\underline{i}}$ as $i + \infty$, where $x_{n_{\underline{i}}}^{*} = (x_{n_{\underline{i}}1}, x_{n_{\underline{i}}2}, \dots, x_{n_{\underline{i}}q})$, (ii) $\xi(x) \in C$ (a, δ) for some $\delta > 0$, x_{0} integer,
- (iii) let $\{J_{\underline{I}}\}_{\underline{I}=1}^3$ be a partition of the set $J=\{1,2,\ldots,q\}$ satisfying the following conditions for a fixed j₀ e J₂

where $a_j \neq 0$, for all $j \in J_2$,

$$\sum_{i=1}^{\infty} (x_{n_i j_0} - a_{j_0})^{2r_0} = -, \qquad (2.9)$$

$$(x_{n_{i}j} - a_{j})^{r_{0}+1} = o((x_{n_{i}j_{0}} - a_{j_{0}})^{r_{0}}), j \in J_{3}.$$
 (2.10)

$$\frac{r-1}{1 + m} | \sum_{k=0}^{r-1} s_i(k,j_0) + s_i(r,j_0,T_{r3}) + \psi'\psi_{j_0}^{(r)}(a) | > 0$$
 (2.11)

for all y with $y'y_{j_0}^{(r)}(z) \neq 0$ where $s_i(k,j_0)$, $s_i(r,j_0,T_{r3})$ and T_{r3} are defined in (2.2), (2.3) and (2.7). Then the vectors

$$y_{j_0}^{(r)}(\underline{a}) = \sum_{\underline{t}_r \in T_{r2}} \alpha_{j_1} \cdots \alpha_{j_r} \frac{\partial^r \underline{f}(\underline{a})}{\partial x_{j_1} \cdots \partial x_{j_r}}, \quad r = 1, 2, \dots, r_0$$

are consistent directions.

Proof: According to Theorem 1 of Wu (1980), we only need to prove that for any fixed $1 \le r \le r_0$

$$\sum_{i=1}^{\infty} \left[\psi^{i} \xi(\xi_{n_{i}}) \right]^{2} = \infty \text{ for any } \psi \text{ with } \psi^{i} \psi_{j_{0}}^{(r)}(a) \neq 0 \text{ .}$$

Consider a Taylor series expansion of $f(\mathbf{x}_{\mathbf{n}_i})$ at a

$$\xi(\xi_{n_{\underline{i}}}) = \sum_{k=0}^{r} \left\{ (\xi_{n_{\underline{i}}} - \underline{a})^{\nabla} \right\}^{k} \xi(\underline{a}) / k \mathbf{1} + \left[(\xi_{n_{\underline{i}}} - \underline{a})^{\nabla} \right]^{r+1} \xi(\xi_{\underline{i}}) / (r+1) \mathbf{1}$$

where $\xi_{i} = \underline{x}_{n_{i}} + \theta^{(i)}(\underline{x}_{n_{i}} - \underline{a}), \ \theta^{(i)} = \operatorname{diag}(\theta_{1}^{(i)}, \dots, \theta_{q}^{(i)}), \ 0 \le \theta_{j}^{(i)} \le 1$ for $1 \le j \le q$ and all i. Thus,

$$\sum_{i=1}^{\infty} \left[\psi^{i} \xi(\xi_{n_{i}}) \right]^{2} = \sum_{i=1}^{\infty} \left(x_{n_{i}} j_{0} - a_{j_{0}} \right)^{2r} \left[\sum_{k=0}^{r} \frac{\psi^{i} \left[(\xi_{n_{i}} - \xi)^{\nabla} \right]^{k} \xi(\xi)}{k! \left(x_{n_{i}} j_{0} - a_{j_{0}} \right)^{r}} \right]^{2} + \frac{\psi^{i} \left[(\xi_{n_{i}} - \xi)^{\nabla} \right]^{r+1} \xi(\xi_{i})}{(r+1)! \left(x_{n_{i}} j_{0} - a_{j_{0}} \right)^{r}} \right]^{2}$$

$$= \sum_{i=1}^{\infty} \left(x_{n_{i}} j_{0} - a_{j_{0}} \right)^{2r} \left[\sum_{k=0}^{r} s_{i}(k, j_{0}) + R_{i}(r+1, j_{0}) \right]^{2}$$

$$= \sum_{i=1}^{\infty} \left(x_{n_{i}} j_{0} - a_{j_{0}} \right)^{2r} s_{ir}^{2}, \qquad (2.12)$$

where

$$R_{\underline{i}}(r+1,j) = \frac{\underline{\psi}^{t}((\underline{x}_{n_{\underline{i}}} - \underline{a})^{\overline{y}})^{r+1}\underline{f}(\underline{\xi}_{\underline{i}})}{(r+1)!(\underline{x}_{n_{\underline{i}}j_{0}} - \underline{a}_{j_{0}})^{r}}.$$

By assumption (ii), there exists an M > 0, such that

$$\sup_{\mathbf{g}\in\mathbf{M}(\mathbf{g},\mathbf{\delta})} \left| \frac{\partial^{x+1} \mathbf{f}_{\mathbf{t}}(\mathbf{g})}{\partial \mathbf{x}_{\mathbf{j}} \cdots \partial \mathbf{x}_{\mathbf{j}_{x+1}}} \right| \leq \mathbf{M}, \qquad \mathbf{t} = 1, 2, \dots, p.$$

From Cauchy-Schwarz inequality, (2.8) and (2.10),

 $R_{\underline{i}}(r+1,j_0) \leq (constant) \mathbb{I}\left[\left(\underline{x}_{n_{\underline{i}}} - \underline{a}\right) \overline{V}\right]^{r+1} \underline{f}(\underline{\xi}_{\underline{i}}) \mathbb{I}/|x_{n_{\underline{i}}j_0} - a_{j_0}|^r + 0 \text{ as } \underline{i} + \infty.$ We decompose $S_{\underline{i}}(r,j_0)$ into two parts

$$s_i(r,j_0) = s_i(r,j_0,T_{r1} \cup T_{r2}) + s_i(r,j_0,T_{r3})$$
.

From (2.8), it is easy to see that

$$s_1(r,j_0,r_{r_1} \cup r_{r_2}) + \psi' = \sum_{\xi_r \in r_2} a_{j_1} \cdots a_{j_r} \frac{\partial_r \xi(\xi)}{\partial x_{j_1} \cdots \partial x_{j_r}} = \psi' \psi_0^{j_0}(\xi)$$

By assumption (2.11), there exist N_0 and $\eta > 0$ such that for $i > N_0$, $S_{ir}^2 > \eta$. Since (2.9) implies $\sum_{i=1}^{\infty} (x_{n_i j_0} - a_{j_0})^{2r} = 0$ for any $r < r_0$, from (2.12), the required result is proved.

The linear space spanned by $y_{j_0}^{(r)}(a)$, is independent of the choice of $j_0 \in J_2$. In fact, for any $j_1 \in J_2$, $j_1 \neq j_0$, let

$$\underline{\mathbf{y}}_{j_1}^{(\mathbf{r})}(\underline{\mathbf{a}}) = \sum_{\underline{\mathbf{b}}_{\mathbf{r}} \in \mathbf{r}_{\mathbf{r}^2}} \alpha_{j_1}^{\underline{\mathbf{a}}} \cdots \alpha_{j_{\mathbf{r}}}^{\underline{\mathbf{a}}} \frac{\partial^{\mathbf{r}} \underline{\mathbf{f}}(\underline{\mathbf{a}})}{\partial \mathbf{x}_{j_1} \cdots \partial \mathbf{x}_{j_{\mathbf{r}}}}$$

where

$$a_{j}^{*} = \lim_{i \to \infty} (x_{n_{i}j} - a_{j})/(x_{n_{i}j_{1}} - a_{j_{1}}), \quad j \in J_{2}.$$

It is easy to see that

$$y_{j_1}^{(r)}(a) = (a_{j_0}^*)^r y_{j_0}^{(r)}(a)$$
 for $1 \le r \le r_0$.

Thus the two vectors span the same linear subspace.

When $J_1 = J_3 = \phi$, the empty set, all the components of x_0 converge at the same rate and Theorem 2 takes a simpler form.

Corollary 1. Suppose (i) and (ii) of Theorem 2 hold and for some $1 \le j_0 \le q$

$$\lim_{\substack{j \to \infty \\ i + \infty}} \frac{x_{n_{i}j_{0}} - a_{j}}{x_{n_{i}j_{0}} - a_{j_{0}}} = \alpha \quad \text{for } 1 < j < q$$
 (2.13)

where $\alpha_j \neq 0, \infty$,

$$\sum_{i=1}^{\infty} (x_{n_i j_0} - a_{j_0})^{2r_0} = \infty.$$
 (2.14)

Then

 $[aV]^{T}f(a)$ are consistent directions for $r = 1, 2, ..., r_{0}$

where

$$\underline{a} = (a_1, \dots, a_q)$$
 and $[\underline{a}^{\nabla}]^r \underline{f}(\underline{a}) = \sum_{\underline{t}_r \in T_r} a_{\underline{t}_1} \cdots a_{\underline{t}_r} \frac{\partial^r \underline{f}(\underline{a})}{\partial x_{\underline{t}_1} \cdots \partial x_{\underline{t}_r}}$.

Proof: It is sufficient to prove that (2.11) holds for the case under consideration. In fact, since $T_{r3} = \phi$, $S_1(r,j_0,T_{r3}) = 0$, and

$$\begin{split} s_{i}(k,j_{0}) &= \frac{\underline{y}^{*}}{(x_{n_{i}}j_{0} - a_{j_{0}})^{r-k}} \sum_{\xi_{k} \in T_{k}} \frac{(x_{n_{i}}j_{1} - a_{j_{1}}) \cdot \cdot \cdot \cdot (x_{n_{i}}j_{k} - a_{j_{k}})}{(x_{n_{i}}j_{0} - a_{j_{0}}) \cdot \cdot \cdot \cdot (x_{n_{i}}j_{0} - a_{j_{0}})} \frac{\partial^{k} \xi(\underline{a})}{\partial x_{j_{1}} \cdot \cdot \cdot \cdot \partial x_{j_{k}}} \\ &= \frac{\underline{y}^{*}}{(x_{n_{i}}j_{0} - a_{j_{0}})^{r-k}} s_{i}^{*}(k,j_{0}) \quad \text{for } k = 0,1,...,r \ . \end{split}$$

From (2.13)

$$s_{\underline{i}}^{*}(k,j_{0}) + [gV]^{k}f(\underline{a}), \qquad k = 1,2,...,r,$$

 $s_{\underline{i}}^{*}(0,j_{0}) = f(\underline{a}).$

Let k_0 be the first k with $\psi'[gV]^k f(a) \neq 0$. From $\psi'[gV]^r f(a) \neq 0$, we have $k_0 \leq r$. Thus, the S_{ir}^2 in (2.12) are dominated by the leading term $S_i(k_0,j_0)$, which is bounded away from zero as $i + \infty$. Therefore (2.11) is satisfied.

Wu and Wang (1982) gave a more direct proof of Corollary 1.

If $J_3 = \phi$ and $J_2 = \{j_0\}$ in Theorem 2, we obtain immediately the following Corollary.

Corollary 2. Under conditions (i) and (ii) of Theorem 2 and the following conditions:

for a fixed jo

$$x_{n_{i}j} - a_{j} = o(x_{n_{i}j_{0}} - a_{j_{0}})$$
 for all $j \neq j_{0}$, (2.15)

$$\sum_{i=1}^{\infty} (x_{n_i j_0} - a_{j_0})^{2r_0} = \infty, \qquad (2.16)$$

$$\frac{\lim_{i\to\infty}\left|\sum_{k=0}^{r-1} s_{i}(k,j_{0}) + w^{i} \frac{\partial^{r}f(a)}{\partial x_{j_{0}}^{r}}\right| > 0}{\delta x_{j_{0}}^{r}}$$
for all w with $w^{i} \frac{\partial^{r}f(a)}{\partial x_{i}^{r}} \neq 0$ and $r = 1,2,...,r_{0}$ (2.17)

where

$$\frac{\partial^{r} f(\underline{a})}{\partial x_{j_{0}}^{r}} = \left(\frac{\partial^{r} f_{1}(\underline{a})}{\partial x_{j_{0}}^{r}}, \dots, \frac{\partial^{r} f_{p}(\underline{a})}{\partial x_{j_{0}}^{r}}\right)^{r}.$$

Then

$$\frac{\partial^{r} f(a)}{\partial x_{j_{0}}^{r}}$$
 are consistent directions for $r = 1, 2, ..., r_{0}$.

Similarly, for $J_1 = \phi$ and $J_2 = \{j_0\}$, analogous results readily obtain.

For multiple regression, we only need to consider a special case of Theorem 2, i.e. $r_0 = 1$. Two cases are considered below as corollaries.

Corollary 3. Suppose (i), (ii) and (2.8), (2.9), (2.10) of Theorem 2 for $r_0 = 1$ hold, and

$$\frac{\lim_{i \to \infty} \left| \frac{\mathcal{R}' f(\underline{a})}{\kappa_{n_i j_0} - a_{j_0}} + \mathcal{R}' \int_{j \in \mathcal{I}_3} \frac{\partial f(\underline{a})}{\partial \kappa_j} \frac{(\kappa_{n_i j} - a_j)}{(\kappa_{n_i j_0} - a_{j_0})} + \mathcal{R}' \int_{j \in \mathcal{I}_2} \alpha_j \frac{\partial f(\underline{a})}{\partial \kappa_j} \right| > 0$$
 (2.18)

for all w with

$$\underline{w}' \quad \sum_{j \in J_2} \alpha_j \frac{\partial \xi(\underline{a})}{\partial x_j} \neq 0$$

Then

$$\sum_{j \in \mathbb{J}_2} \alpha_j \frac{\partial \xi(a)}{\partial x_j}$$
 is a consistent direction.

From Corollaries 1 and 2 we observe that (2.11) holds automatically for $r_0 > 1$ only if J_1 and J_3 are both empty. Such is not the case for $r_0 = 1$. It is easy to see that if $J_3 = \phi$, (2.18) is automatically satisfied, and thus the following corollary. Corollary 4. Suppose (i) and (ii) of Theorem 2 hold for $r_0 = 1$ and (iii) there exists a partition J_1 and J_2 of the set $J = \{1, 2, ..., q\}$ such that for a fixed $j_0 \in J_2$,

$$\lim_{\substack{i \to \infty}} \frac{x_{n_i j} - a_j}{x_{n_i j_0} - a_{j_0}} = \begin{cases} 0 & j \in J_1 \\ \alpha_j & j \in J_2 \end{cases}$$

where $\alpha_{i} \neq 0, \infty$, and

$$\sum_{i=1}^{\infty} (x_{n_i j_0} - a_{j_0})^2 = \infty.$$

Then

$$\sum_{j \in J_2} \alpha_j \frac{\partial f(a)}{\partial x_j}$$
 is a consistent direction.

The following theorem shows that by further partitioning J_3 into disjoint subsets more consistent directions will be obtained.

Theorem 3. Suppose (i) and (ii) of Theorem 2 hold, and there exists a partition $\{J_{\ell}\}_{\ell=1}^h$ of the set $J = \{1, 2, ..., q\}$ satisfying the following conditions:

(iii) For a fixed $j_{\underline{\ell}} \in J_{\underline{\ell}}$, $\underline{\ell} = 1, 2, ..., h$

$$\lim_{i\to\infty} \frac{x_{n_ik} - a_k}{x_{n_ij_\ell} - a_{j_\ell}} = \alpha_{kj_\ell\ell} \text{ for all } k \in J_\ell$$

where akj. *0, ...

(iv) For any $j \in J_{\underline{x}}$, $k \in J_{\underline{x}+1}$, $\underline{x} = 1, 2, ..., h - 1$

$$x_{n_{i}j} - a_{j} = o(x_{n_{i}k} - a_{k})$$
,

(v) There exists an $h_0 \le h$ such that for $h_0 \le t \le h$, there exists an integer r_t s.t.

$$(x_{n_{\underline{i}}k} - a_{\underline{k}})^{x_{\underline{i}}+1} = o((x_{n_{\underline{i}}j} - a_{\underline{j}})^{x_{\underline{i}}}), \quad k \in J_{h}, j \in J_{\underline{i}},$$

$$\sum_{\underline{i}=1}^{\infty} (x_{n_{\underline{i}}j} - a_{\underline{j}})^{2x_{\underline{i}}} = \infty, \quad j \in J_{\underline{i}}, \quad k > h_{0}.$$

(vi) For $h_0 \le l \le h$

$$\frac{\lim_{i\to\infty}\sum_{k=0}^{r-1}s_{\underline{i}}(k,j_{\underline{k}})+s_{\underline{i}}(r,j_{\underline{k}},T_{\underline{k}})+\psi^{*}\psi^{*}_{\underline{j}_{\underline{k}}}(a)|>0$$

for y with $y^i y_{j_{\underline{z}}}^{(r)}(\underline{a}) \neq 0$, $r = 1, 2, ..., r_{\underline{z}}^*$

where $T_k^* = \{(j_1, \dots, j_r) : (j_1, \dots, j_r) \in T_r \text{ for at least one } j_t \in \bigcup_{k=k+1}^h J_k\},$ $T_k^* = \min\{T_t : t > k\}.$

Then the vectors

$$y_{j_{1}}^{(r)}(a) = \sum_{j_{1},...,j_{r} \in \mathcal{I}_{L}} \alpha_{j_{1}j_{1}L} \cdots \alpha_{j_{r}j_{L}L} \frac{\partial^{r} \xi(a)}{\partial x_{j_{1}} \cdots \partial x_{j_{r}}},$$

$$x = h_{0}, h_{0} + 1,...,h, \quad r = 1,2,...,r_{L}$$

are consistent directions.

Proof: For any fixed J_{ℓ} , $h_0 \le \ell \le h-1$, $j_0 \in J_{\ell}$, we regard J_{ℓ} , j_{ℓ} , $\bigcup_{k=1}^{\ell-1} J_k$ and $\bigcup_{k=\ell+1}^{h} J_k$ as J_2 , j_0 , J_1 and J_3 , respectively, in Theorem 2. From Theorem 2 we conclude that $\bigvee_{j=\ell+1}^{\ell-1} (a_j)$ are consistent directions for $\ell=h_0,h_0+1,\ldots,h-1$, and $\ell=1,2,\ldots,r_{\ell}$. That $\bigvee_{j=\ell+1}^{\ell-1} (a_j)$ are consistent directions for $\ell=1,2,\ldots,r_0$ follows from Theorem 2 with $J_3=0$.

By combining the results in Theorems 1 and 3 for each limit point of the design sequence and using Theorem 2 of Wu (1980), we obtain the following main theorem.

Define $L\{a_1,\dots,a_t\}$ to be the subspace spanned by vectors a_1,\dots,a_t .

Theorem 4. Suppose a_j , $j=1,\dots,k$, are k distinct limit points of $\{x_i\}_{i=1}^{\infty}$ and $y_{\ell}(a_j)$, $j=1,\dots,k$, $\ell=1,\dots,t_j$, are the consistent directions obtained from Theorem 3, then

$$s(\xi) = \sum_{j=1}^{k} A_{j}(\xi) \bullet B_{k+1}(\xi)$$

where

$$\begin{split} A_{j}(\xi) &= L\{\xi(a_{j}), \ \psi_{\xi}(a_{j}), \ \ell = 1, \dots, \ell_{j}\}, \qquad j = 1, \dots, k \ , \\ B_{k+1}(\xi) &= \{ \psi \in \left[\sum_{j=1}^{k} A_{j}(\xi) \right]^{\perp} : \sum_{i=1}^{m} \left[\psi^{i} \xi(x_{i}) \right]^{2} = m \\ & \text{for any } \psi \in \left[\sum_{i=1}^{k} A_{j}(\xi) \right]^{\perp} \text{ and } \psi^{i} \psi \neq 0 \} \ . \end{split}$$

There is no loss of generality in assuming finite $\,k\,$ in Theorem 4 as was noted in Wu and Wang (1982).

3. Examples

In this section the general results developed heretofore will be applied to some regression models. These examples show that our conditions are easier to verify than the more typical condition $b'(X_2'X_2)^{-1}b \to 0$.

(i) Multiple regression

$$y = \theta' f(x) + \varepsilon \tag{3.1}$$

where $\theta' = (\theta_0, \theta_1, \dots, \theta_{q-1}), \ x' = (1, x_1, \dots, x_{q-1}), \ \xi(x) = x.$

For the design sequence $x_i' = (x_{i0}, x_{i1}, \dots, x_{iq-1}), x_{i0} = 1$,

 $i = 1, 2, ..., x_i + a = (a_0, a_1, ..., a_{n-1})^t, a_0 = 1.$

(a) If $x_{ij} = a_j + i^{-1/2}$, j > 1, Corollary 4 with $\alpha_j = 1$, j = 1, 2, ..., q - 1, $r_0 = 1$, $J_1 = \{0\}$, $J_2 = \{1, ..., q - 1\}$ applies. From Theorem 1 and Corollary 4, $f(a) = a, \sum_{j=1}^{q-1} \frac{\partial f(a)}{\partial x_j} = (0, 1, ..., 1)^{\frac{1}{2}} \text{ are consistent directions.}$

(c) If $x_{ij} = a_j + i^{-(j+1)^{-1}}$, j > 1. It is easy to verify that $J_{\underline{g}} = \{\underline{t}\}$, $\underline{t} = 0, 1, 2, ..., q - 1$, $h_0 = [q/2]$, where [x] is the largest integer less than or equal to x, $J_{\underline{g}}$ and h_0 are defined in Theorem 3. Therefore $\frac{\partial \underline{f}(\underline{a})}{\partial x_j} = \underline{e}_j = (0, ..., 0, 1, 0, ..., 0)^{*}$, j = [q/2], ..., q, and \underline{a} are consistent directions. (ii) Multiple polynomial regression

$$y = \theta' f(x) + \varepsilon \tag{3.2}$$

where $f_j(x)$, j = 1,...,p, are monomials in x of degree less than or equal to d. If $f_i(x) \neq f_i(x)$ for $i \neq j$, then p = (d+q)i/(diqi).

We will describe in more detail the general results to be obtained for the following quadratic polynomial regression model in two variables:

$$y = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1 x_2 + \theta_4 x_1^2 + \theta_5 x_2^2 + \varepsilon$$
 (3.3)

and limit point $a = (a_1, a_2)$.

(a) If $x_{ij} = a_j + i^{-1/4}$, $1 \le j \le q$, Corollary 1 with $\alpha_j = 1$, $j = 1, \dots, q$ and $r_0 = 2$ applies. Thus $f(a_j)$, $f(a_j)$ and $f(a_j)$ and $f(a_j)$ and $f(a_j)$ are consistent directions for model (3.2). In particular, for model (3.3), the three consistent directions are $f(a_j) = (1, a_1, a_2, a_1 a_2, a_1^2, a_2^2)^{\frac{1}{2}},$

$$\frac{\partial \xi(\underline{a})}{\partial x_{1}} + \frac{\partial \xi(\underline{a})}{\partial x_{2}} = (0, 1, 1, a_{1} + a_{2}, 2a_{1}, 2a_{2})',$$

$$\sum_{i,j=1}^{2} \frac{\partial^{2} \xi(\underline{a})}{\partial x_{i} \partial x_{j}} = (0, 0, 0, 2, 2, 2)'.$$

(b) If $x_{ij} = a_j + i^{-1/2}$ for $1 \le j \le j_0$ and $= a_j + i^{-1/3}$ for $j_0 \le j \le q$, then $J_1 = \{1, 2, ..., j_0\}$, $J_2 = \{j_0 + 1, ..., q\}$, $r_1 = r_2 = 1$ in Theorem 3. Therefore

f(a), $\sum_{j=1}^{j} \frac{\partial f(a)}{\partial x_j}$ and $\sum_{j=j+1}^{q} \frac{\partial f(a)}{\partial x_j}$ are consistent directions. For model (3.3) and

 $j_0 = 1$, the last two consistent directions are

$$\frac{\partial f(a)}{\partial x_1} = (0,1,0,a_2,2a_1,0),,$$

$$\frac{\partial f(a)}{\partial x_2} = (0,0,1,a_1,0,2a_2).$$

(c) If $x_{ij} = a_j + i^{-1/(j+1)}$, j = 1, 2, ..., q, it is easy to verify that $J_{\underline{x}} = \{\underline{t}\}$, $\underline{t} = 1, 2, ..., q$, $h_0 = \left[\frac{q+1}{2}\right]$, $r_{\underline{x}} = \min\left\{\left[\frac{\underline{x}+1}{2}\right], \left[\frac{\underline{x}+1}{q-\underline{x}}\right]\right\}$ and $r_{\underline{x}}^* = 1$ for all $\underline{t} > h_0$ where $J_{\underline{x}}$, h_0 , $r_{\underline{x}}$ and $r_{\underline{x}}^*$ are defined in Theorem 3. Thus we know that $\underline{t}(\underline{a})$, $\frac{\partial \underline{t}(\underline{a})}{\partial x_1}$, $\underline{j} = [(q+1)/2], ..., q$, are consistent directions.

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

The consistent directions of the least squares estimators in a linear model are defined to be the linear combinations of parameter estimates that are asymptotically consistent. When the design variable is univariate and the regression function is smooth, consistent directions are characterized in previous papers (Wu, 1980; Wu and Wang, 1982) in terms of the convergence rates of the design sequence to its limit points. Extensions of these results to multivariate design variables are considered in the present paper.

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